Automated extraction of agronomic parameters in orchard plots from high-resolution imagery

J. Recio, T. Hermosilla and L.Á. Ruiz

Geo-Environmental Cartography and Remote Sensing Group - Universitat Politècnica de València, Camino de vera s/n 46022 Valencia, (Spain)

Abstract. The availability of high spatial resolution images obtained from aerial and satellite sensors together with the development of new image analysis methods are providing an important impulse to precision agriculture techniques and applications. We describe an automated methodology for the extraction of agronomic parameters from tree orchard plots based on the use of high-resolution remotely sensed imagery, which can be further used to increase the efficiency of irrigation and agricultural plot management in the SUDOE area. These methods are based on parcel-based image analysis, and a variety of parameters are obtained including tree detection, location and counting, planting patterns, tree crown, vegetation cover and others. Since common data and image processing techniques are used, they can be easily implemented in production processes and cover large agricultural areas. The methods are tested on citrus orchard plots located in Valencia (Spain), showing a good performance in particular for adult trees. In addition to the particular use of the ground cover for the estimation of water requirement, these parameters can also be used as support tools for agricultural inventories or database updating, allowing for the reduction of field work and manual interpretation tasks.

Keywords. Irrigation efficiency – Remote sensing – Parcel-based image analysis – Tree detection – High-resolution images.

Extraction automatique de paramètres agronomiques pour les parcelles de vergers à l'aide d'imagerie à haute résolution

Résumé. *La disponibilité d'images à haute résolution spatiale obtenues par des capteurs aériens et satellitaires, parallèlement au développement de nouvelles méthodes d'analyse d'images, ont donné un important élan aux techniques et applications de l'agriculture de précision. Nous décrivons une méthodologie automatique pour l'extraction de paramètres agronomiques concernant les parcelles de vergers, basée sur l'emploi d'imagerie à haute résolution obtenue par télédétection, qui peut être d'utilité pour accroître l'efficience de l'irrigation et de la gestion des parcelles agricoles dans la région SUDOE. Ces méthodes sont basées sur l'analyse d'images au niveau de la parcelle, obtenant une série de paramètres dont la détection, la localisation et le dénombrement des arbres, la configuration de la plantation, la couronne des arbres, le couvert de végétation et autres. Puisque l'on utilise des données et techniques courantes de traitement d'images, elles sont facilement applicables aux processus de production et peuvent concerner de vastes zones agricoles. Les méthodes sont testées dans des vergers d'agrumes situés à Valencia (Espagne), et montrent de bons résultats en particulier pour les arbres adultes. En plus de leur utilisation particulière pour le couvert végétal afin d'estimer les besoins en eau, ces paramètres peuvent aussi être utilisés comme outils d'appui pour l'actualisation des inventaires agricoles ou des bases de données, permettant ainsi de réduire le travail de terrain et les tâches d'interprétation manuelle.*

Mots-clés. *Efficience de l'irrigation – Télédétection – Analyse d'images basée sur la parcelle – Détection des arbres – Images à haute résolution.*

I – Introduction

The availability of high-spatial resolution aerial and satellite digital images opened new outlooks for the automatic extraction of information in the domains of agriculture and forestry. Traditionally, agricultural parameters such as the number of trees, spatial distribution and crown size or tree canopy cover have been estimated by photointerpretation, relating the image-derived information with supporting field data. As stated in a previous chapter, algorithms for the automatic extraction of these parameters in large irrigation areas, in particular the tree canopy cover, would provide valuable information for a better estimation of crop coefficient (K_c) and its application to calculate crop water requirements.

Remote sensing technology has been used to obtain information about crop condition in precision agriculture (Viau *et al.*, 2005). Also, spectral data collected by multi-spectral optical sensors has been widely used to obtain different types of vegetation indices, which can be related to biophysical parameters that provide information about plant status or vegetation density (Mazzetto *et al.*, 2010). When remote sensing is used in conjunction with *variable rate technology*, water and chemicals can be selectively applied in the soil, enabling a cost-effective and environmental-friendly management (Du *et al.*, 2005). The detection and location of individual trees from images enables to improve the classification of different species through the analysis of within-crown spectral data, spatial distribution and crown shape (Pouliot *et al.*, 2002; Erikson, 2004). Further description of trees in an agricultural plot can be applied as well for the management and updating of agricultural inventories and land use databases by means of parcel-based image classification (Recio, 2009). Wang *et al.* (2007) related K_c of pecan orchards with the tree size and spacing (effective canopy cover, ECC) using image analysis techniques from images obtained from a balloon and satellite, rendering a model and concluding that this equation can help to get more accurate estimates of irrigation requirements for pecan open-canopy orchards.

In this chapter, we describe a methodology developed in the frame of the TELERIEG project (Interreg IVb Sudoe, project no. SOE1/P2/E082) for the automated extraction of agronomic parameters from high-resolution aerial and satellite images. These parameters may be used in large irrigation areas to improve crop requirement estimation, but also in other applications such as crop classification and change monitoring at plot level, agricultural inventories or detection of crop abandonment.

II – Data and study area

Digital orthoimages acquired in June 2006 using a Vexcel Ultracam-D with a mean flight height of 4,500 meters over the mean terrain height were used as basic data. Spatial resolution of images was 0.5 m/pixel, 8 bits quantization, and three spectral bands: near-infrared (NIR), red and green. The images were provided in the framework of the *Plan Nacional de Ortofotografía Aérea* (PNOA), and they were provided orthorectified, geo-referenced, panchromatic and multi-spectral band fused, and radiometrically adjusted. The limits of the plots were obtained from cadastral cartography at a scale of 1:2000 in *shapefile* format, produced by the Spanish General Directorate for Cadastre.

The study area is located in the municipality of Llíria in the province of Valencia, Spain. The area is mainly covered by citrus orchards, followed by horticulture crops, fruit orchards and carob trees. The methodology was tested over citrus crops. A total of 300 plots were selected to perform the study, occupying an area of 265 ha.

III – Tree detection and delineation

Several approaches have been reported in the literature regarding the automated location of individual trees and crown delineation, i.e. radiance peak filtering (Dralle and Rudemo, 1997; Wulder *et al.*, 2000), valley following (Gougeon, 1995), template matching (Pollock, 1996), and clustering (Culvenor, 2002).

Local maximum filtering methods are based on the assumption that reflectance is highest at the tree apex and decreases towards the crown edge. These approaches identify the peaks in image intensity representing the location of each tree crown but not its outline. A kernel is moved over the image and trees are located where the central digital value in the window is higher than all other values. The size of the kernel can be fixed according to the mean size of trees or it can be variable depending on the size of each tree (Wulder *et al.*, 2000). Ruiz *et al.* (2007) apply this method over NDVI images using a circular kernel with variable diameter size, ranging from 9 pixels to 23 pixels, and it is determined as the position of the first maximum value of the semivariogram curve computed for each tree crop parcel analyzed.

Contouring or boundary following methods delimit the objects from the background employing the similarity in data values. Valleys of shade or lower intensity areas between tree crowns are identified and remaining tree material is outlined (Gougeon, 1995; Leckie *et al.*, 2003). Template matching approaches are based on mathematical renderings of typologies of crowns for matching with the image brightness to locate trees and determine their crown size (Pollock, 1996). This methodology requires a library of three dimensional model trees, producing omission errors when tree crowns are smaller than the smallest radius in the template library or have irregular crowns (Erikson and Olofsson, 2005). Culvenor (2002) clusters around each local maximum those pixels with digital values greater than a threshold and not belonging to the boundary of the crown obtained as local minima. García Torres *et al.*, (2008) extract the trees by clustering pixels with values within a range defined using a supervised classification. Most of these methods require a certain degree of human intervention providing training samples to the system or defining different thresholds to de used in the tree extraction process.

The methodology used in this project is based on common image processing tools, using image analysis techniques to obtain the information and thresholds needed to perform the tree extraction in an effective way. The procedure is based on clustering and local maxima filtering and is applied in Citrus tree orchards.

1. Tree segmentation methodology

The working unit in the methodology used is the parcel contained in a geospatial database. Each parcel contained in the cartography is analyzed separately, reducing the factors that make difficult the tree extraction in wide areas, such as differences in illumination, calibration of the sensor or in tree canopy spectral response. Besides, the parcel is a spatial unit commonly used in agricultural management being easier to relate the agronomic parameters extracted from the trees and their spatial distribution derived from the imagery to the information contained in agricultural geospatial databases (Ruiz *et al.*, 2011).

Descriptive features derived from the representation of the parcels in the images are obtained in two levels of detail: at parcel level and at tree level.

The extraction of the trees is composed of four steps (Fig. 1):

(i) Pre-processing of the image.

(ii) Unsupervised image classification.

(iii) Identification of classes corresponding to trees in the unsupervised classified image.

(iv) Post-processing of the tree segmentation.

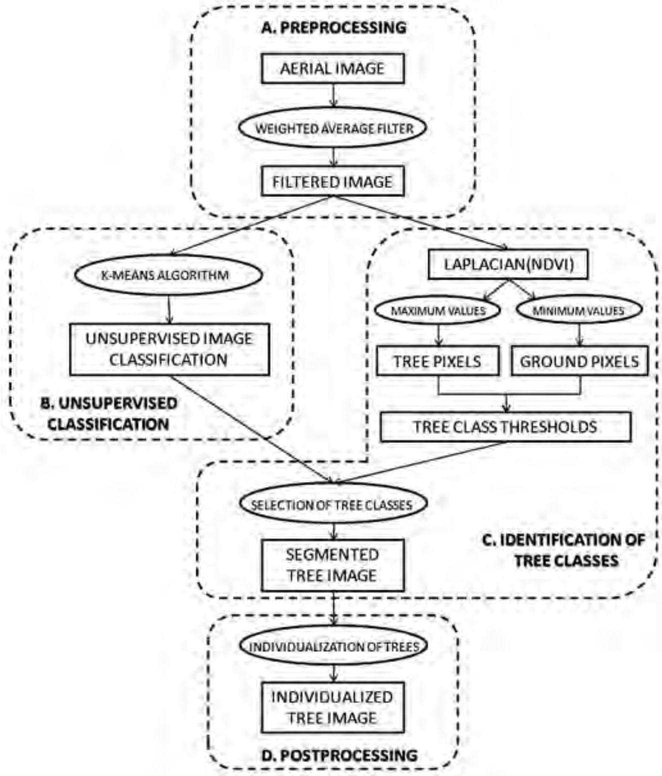


Fig. 1. Overall methodology workflow for tree detection.

A. Pre-processing

Basic geometric correction of the images is essential in order to superimpose the cartography to the images, and the same geographic reference system is required. Radiometric corrections are based on adjustments between different images, usually acquired in different strips in the case of aerial sensors. These techniques can be based on histogram matching, histogram normalisation based on the mean and standard deviation values from different images, regression techniques, etc.

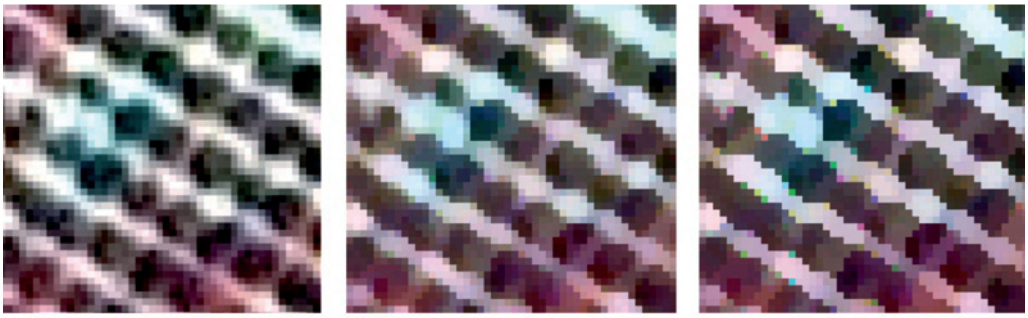
Additionally, tree segmentation in high resolution images is hindered by different factors, such as the internal variability of trees and background, the reduced size of young trees with respect to the spatial resolution of the images, or the transition tree-soil pixels with mixed reflectance values. In order to reduce the effect of these factors in the segmentation process, preprocessing of the images is required. A practical method to reduce the mixed reflectance effect is based on the iterative application of a weighted average filter where the weight of each pixel in the kernel is inversely proportional to the spectral distance to the central pixel (Recio, 2009). The final value for each pixel in the filtered image is obtained using Equation 1.

$$DN'_{i,j} = \frac{\sum_{p=-1}^{1} \sum_{q=-1}^{1} DN_{i+p,j+q} FC_{i+p,j+q}}{\sum_{p=-1}^{1} \sum_{q=-1}^{1} FC_{i+p,j+q}} \qquad (1)$$

where $DN_{i,j}$ is the original digital number of pixel i,j; $DN'_{i,j}$ is the output digital number for this pixel and FC is the filtering coefficient obtained from Equation 2.

$$FC_{i-1,j-1} = 1 - a \cdot \left| DN_{i-1,j-1} - DN_{i,j} \right| \qquad (2)$$

where a is a weighted coefficient of the difference between the digital numbers of the central pixel and the neighbouring pixels. The higher the value of a, the smaller is the influence of neighbouring pixels in the output value of the central pixel. When the filtering coefficient is negative, its value is replaced by 0. If a is greater than 1, then an effect of independent homogenization of objects and background is produced, as well as the enhancement of the borders without blurring the smaller trees. Transition pixels are the most influenced, and their values trend to become similar to those of the object or the background, depending on their similarity in the original image. Figure 2 shows the effect of iteratively applying a filter over an image containing adult citrus trees. Transition pixels disappear and the trees and the background become more homogeneous, facilitating tree segmentation.



Original image **Image filtered (3 iterations)** **Image filtered (6 iterations)**

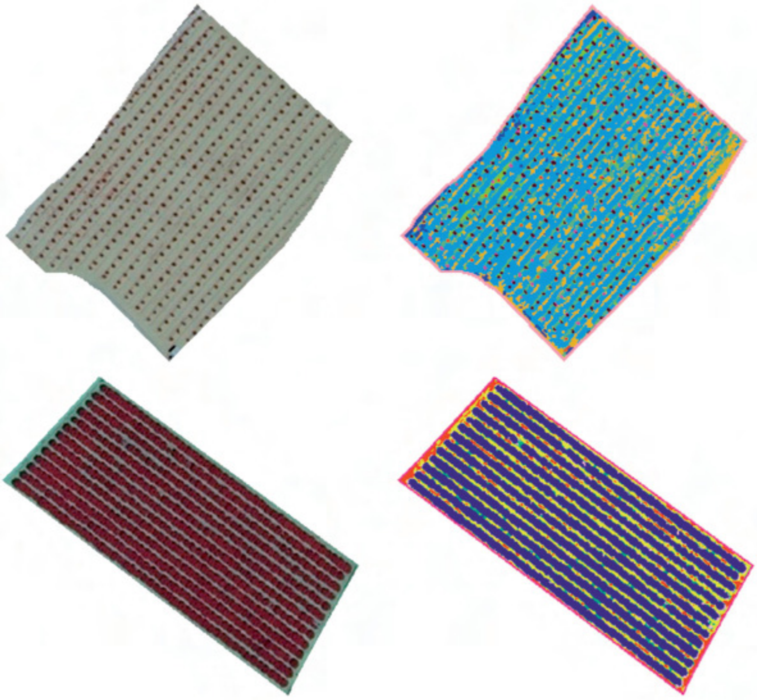
Fig. 2. Detail of the application of the weighted average filter.

B. Unsupervised image classification

The K-means unsupervised classification algorithm is applied to obtain spectrally homogeneous groups of pixels in the image. This algorithm classifies the image pixels into k classes using the criteria that each pixel is assigned to the class with the nearest mean, from an initial set of class prototypes. As the number of classes in each parcel is *a priori* unknown, looking for clusters with a high rate of fragmentation rather than heterogeneous, the number of clusters is initially fixed as ten, even considering that this value is usually greater than the actual number of cover types inside a parcel. Figure 3 shows the results of the unsupervised classification of colour-infrared images applied on two different parcels of the working area.

C. Identification of clusters corresponding to trees

Automated identification of clusters corresponding to trees is achieved by combining the information extracted of the unsupervised classified image and from the original image. In order to parameterise the spectral characteristics of trees and soil, first a 3 × 3 convolution with a Laplacian filter is applied over the NVDI image, then a set of pixels representing these two classes is automatically selected as the maximum and minimum values in the resulting image of the convolved image. Additionally, pixels with maximum and minimum values in the NDVI image are added to the tree and soil sample sets, respectively. Both sample sets are examined to remove



Original image **Unsupervised classification**

Fig. 3. Example of the unsupervised classification of two citrus orchard plots.

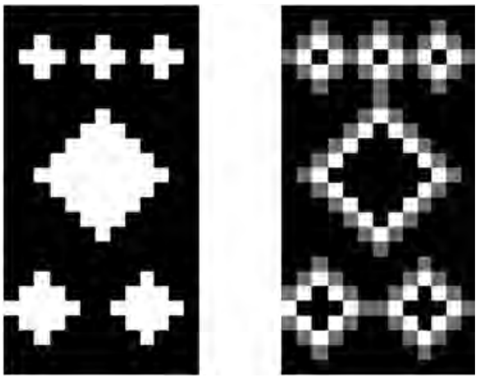
anomalous pixels. Tree pixels with NDVI values lower than the soil pixels mean value are removed from the sample set. Analogously, soil pixels with NDVI values higher than the tree pixels mean value are also removed.

The Normalized Difference Vegetation Index (NDVI) is frequently used to measure and monitor plant growth vegetation cover from multispectral aerial or satellite images and it is calculated with the Equation 3:

$$NDVI = \frac{NIR - R}{NIR + R} \qquad (3)$$

where *NIR* and *R* represent the value of a pixel in the near infra-red and the red channel, respectively. In the red-light region of the electromagnetic spectrum, chlorophyll causes considerable absorption of incoming sunlight, whereas in the near-infrared region, leaf structure creates considerable reflectance. As a result, vigorously growing healthy vegetation has low red-light reflectance and high near-infrared reflectance and hence, high NDVI values. This index ranges from -1.0 to 1.0. Positive NDVI values indicate increasing amounts of green vegetation and negative values indicate non-vegetated areas.

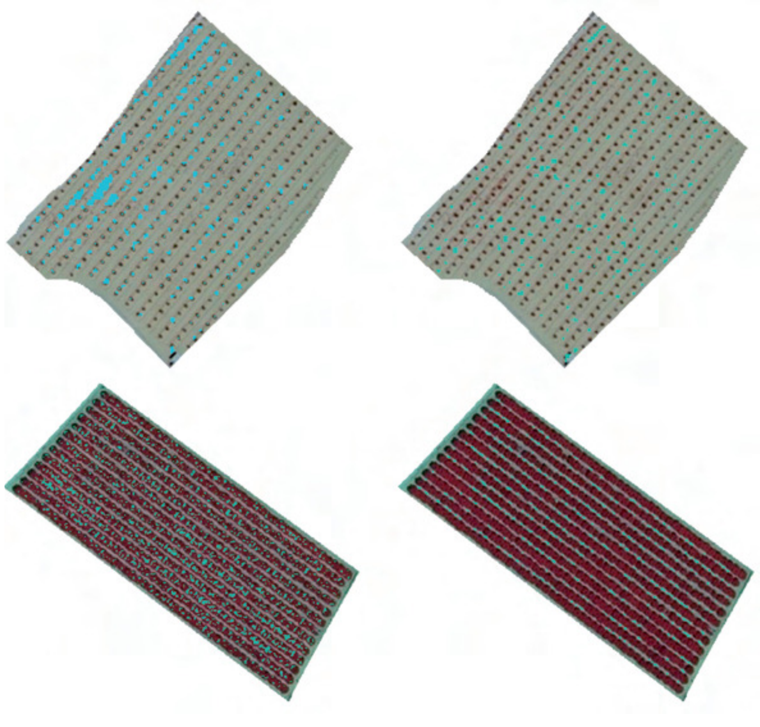
The Laplacian filter is a measure of the second spatial derivative of an image and highlights regions of rapid intensity change and is therefore often used for edge detection. It normally takes a single gray level image as input and produces another gray level image as output (Fig. 4).



a) Original image b) Filtered image

Fig. 4. Example of the convolution of a binary image with a 3x3 Laplacian filter.

The Laplacian filter applied over the NDVI image generates the highest values for the pixels located inside the trees near their boundaries, and the lowest values in the external part of tree boundaries (Fig. 5).



***Tree* pixels** ***Soil* pixels**

Fig. 5. Automatic selection of representative pixels from trees and soil.

Later, the parameters mean and standard deviation of tree and soil pixel values in all bands of the image are computed. In each band, the intersection of the adjusted Gaussian curves defined by tree and soil statistical parameters is determined.

The selection of clusters representing trees in the unsupervised classified image is done by defining two thresholds. Thus, a cluster of pixels is selected as a tree cluster when the mean value of every band is included in the interval limited by two thresholds (Fig. 6). The lower threshold is determined as the mean value of pixels belonging to class tree minus 2.5 times the standard deviation, and the upper threshold is the value obtained in the previous step as the intersection of the modelled Gaussian distribution curves. As a result of this, a binary image is obtained representing a mask of the plot area covered by trees. The Fraction of Vegetation Cover, that is, the proportion of vegetation cover per unit area, is computed as the amount of pixels masked as trees in the binary image divided by the total number of pixels in the parcel.

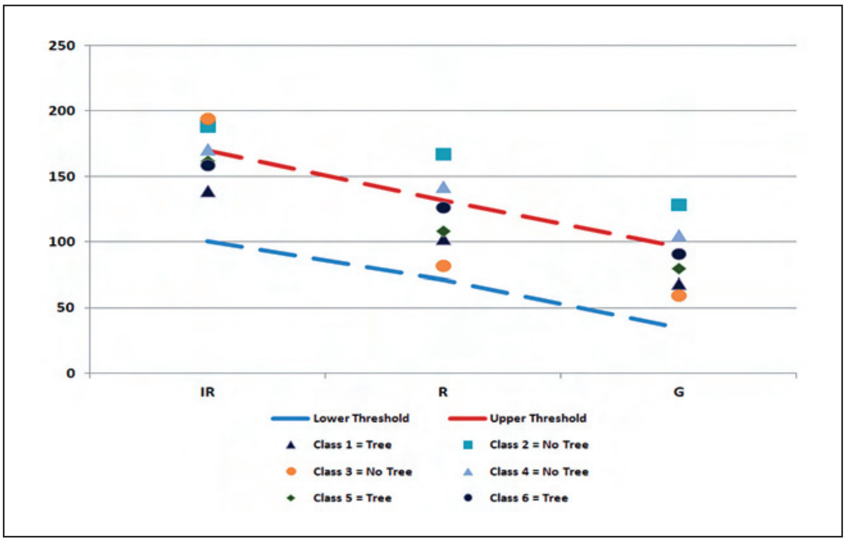


Fig. 6. Identification of classes corresponding to trees.

D. Post-processing

After obtaining image mask representing the area covered by trees by means of image classification or clustering, a post-processing is required in order to isolate the trees and to determine the individual tree cover area. In the case of contiguous trees with overlapping crowns, they are initially detected together in the same cluster, making difficult the tree counting process. The following steps are proposed to individualize the trees (Fig. 7):

1. The minimum distance from every pixel corresponding to a cluster of trees in the binary mask (Fig. 7b) to the background of the image is computed, obtaining a map of distances (Fig. 7c).

2. Over the distances image, an iterative local maxima search is applied using search windows of variable size. The sizes of the search windows range from the minimum to the maximum size of the trees in the area of study. As a result of this, a map of maxima is obtained (Fig. 7d).

3. Around every maximum a circle is drawn centered on it (Fig. 7e). The radius of this circle is the value of the distance from the maximum to the background. Pixels inside this circle will not be selected as maxima in the following steps. The location of the maxima obtained is assumed to correspond to the tree apex. In this process, the maximum size of the search windows should be greater than the biggest tree in the area of study, since an excessive size does not produce errors in the location of trees. However, the minimum size of the search windows should be accurately fixed, otherwise over-detection of trees can occur.
4. When all the maxima are selected, every pixel in the binary mask is assigned to the closest maximum in the same group of pixels. In this way, the groups of pixels in the binary mask are divided in smaller groups corresponding to the actual trees in the parcel (Fig. 7f).

This methodology enables to detect trees with different sizes and to obtain information about their location, quantity and size.

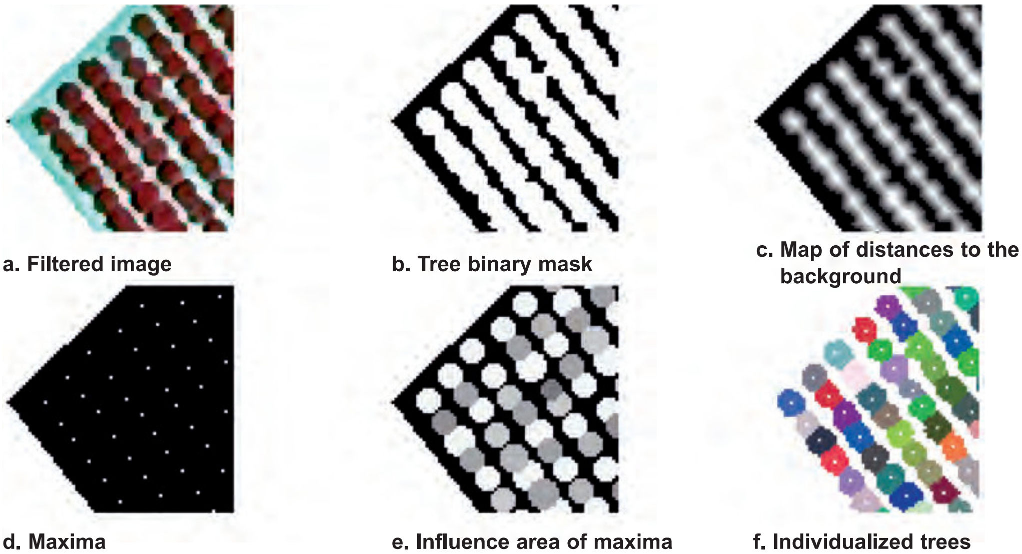


Fig. 7. Process of tree individualization.

IV – Extraction of agronomic parameters

Once finished the methodological procedure for tree detection and individual definition of tree crown cover, a set of agronomic parameters can be derived at tree and parcel levels. In this section we list and describe how they are extracted.

1. Per-tree parameters

Different descriptive parameters or attributes related to the tree location, size, shape and spectral properties can be computed from each cluster of pixels that represent a tree. Table 1 shows some of these parameters that can be directly derived from each segmented tree.

Table 1. Parameters extracted at tree level

Parameter	Abbreviation	Meaning	Units
Identifier	ID	Identifying numeric tag	–
Area of the tree	AT	Number of pixels assigned to the tree cluster	pixels
Coordinates of the centroid of the tree	X, Y	Coordinates of the maximum pixel	column, row
Estimated radius	R	Minimum distance from the maximum pixel to the background	pixels
Accumulated digital number or pixel values	ADN	Summatory of the pixel values inside a tree cluster	DN (pixel value)
Average digital number	MDN		DN (pixel value)

Parameters ADN and MDN can be extracted from all the layers or bands, or any combination or ratio derived from a multispectral image.

2. Per-parcel parameters

A variety of indices or parameters can be derived at parcel level, some of them as a result of generalizing the tree level parameters, and others related to global information (fraction of vegetation cover), or to the arrangement and distribution of trees in the parcel (tree planting pattern). In this sense, particular techniques such as the Hough transform can be used to accurately obtain this type of information.

The Hough transform (Hough, 1962) is a technique commonly used in digital image processing to detect lines or curves. It is based on the transformation of the coordinates of the centroids of trees from a Cartesian image space (X, Y) to a polar coordinate space (ρ, u), where ρ represents the minimum distance from the origin of coordinates to a line, and υ is the angle of the vector from the origin to the closest point of the line with the X axis (Fig. 8). Each point in the Cartesian space is transformed in a sinusoid in the polar space. This sinusoid represents the parameters of the lines passing through that point. The intersection of two sinusoids in the polar space represents the parameters of the particular line passing through these points.

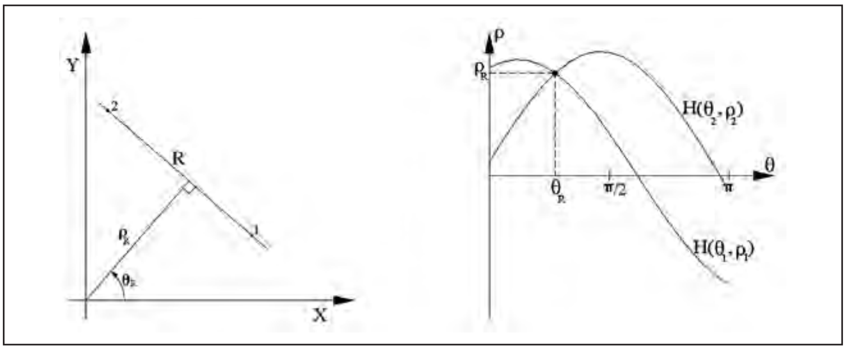
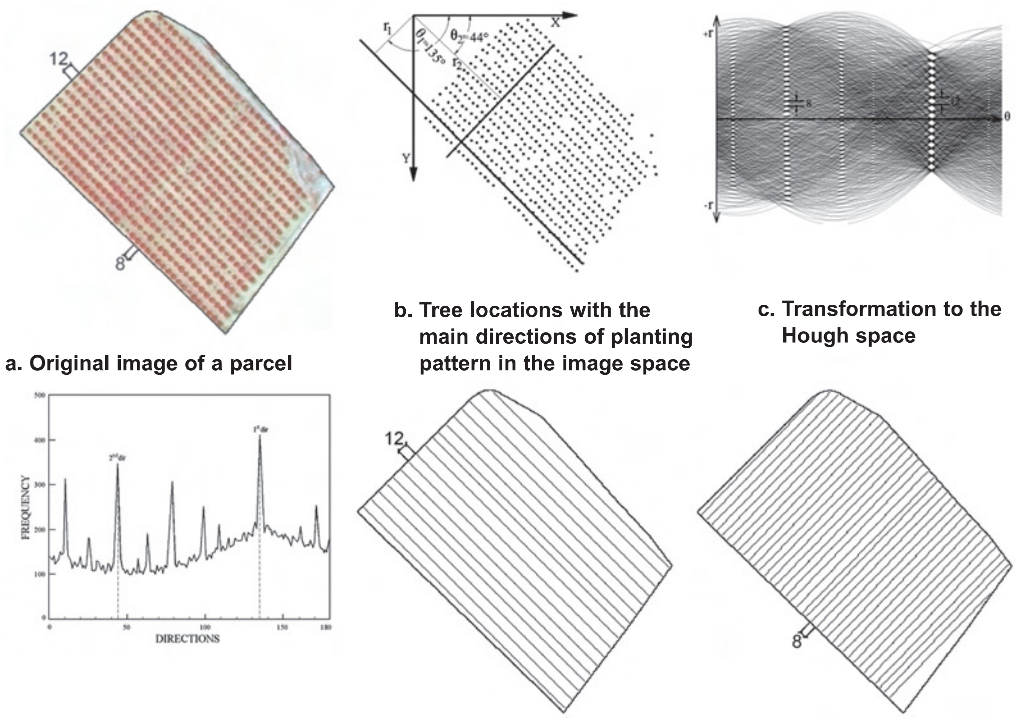


Fig. 8. Representation of a line in Cartesian and in the Hough space.

This transform is applied to the locations of the detected trees in the parcel (Fig. 9b). The results of this transformation are shown in the graph of Fig. 9c, where each intersection represents a line in the image. From this graph, the parameters of the lines passing through a number of points can be obtained. Representing the frequency of the lines in the range of directions from 0º to 179º, the two most frequent directions, corresponding to the two main alignments of trees in the parcel, can be extracted (Fig. 9d). Once the two main directions are known, the median value of the distance between the lines in both directions gives us a measure of the separation of trees in the parcel or planting pattern (Figs 9e and 9f). The final parameters extracted from this methodology are the distance between the tree alignments in the two main directions, and the angular difference between these directions. If this angular difference is close to 90º means that the planting pattern follows a typical rectangular arrangement.



a. Original image of a parcel

b. Tree locations with the main directions of planting pattern in the image space

c. Transformation to the Hough space

d. Histogram of intersections of lines

e. Alignments in the first direction

f. Alignments in the second direction

Fig. 9. Procedure followed to determine the planting pattern from the Hough transform.

Based on this methodology, the set of parameters extracted after generalization of tree level parameters and those related to the geometric arrangements of trees in the parcel are described in Table 2.

Parameters related to pixel values can be extracted from all the layers or bands, or any combination or ratio derived from a multispectral image.

Table 2. Parameters extracted at parcel level

Parameter	Abbreviation	Meaning	Units
Area of the parcel	AP	Number of pixels in the parcel	Pixels
Number of trees	NT	Number of trees in the parcel	Trees
Area covered by trees	ACT	$\sum_{i=1}^{NT} AT_i$	Pixels
Average area of trees	MAT	ACT/NT	Pixels
Fraction of vegetation cover	FVC	ACT/AP	–
Average radius of trees	MR	$\sum_{i=1}^{NT} R_i \Big/ NT$	Pixels
Coefficient of variation of radius	CVR	$\dfrac{\sqrt{\sum_{i=1}^{NT}(R-MR)^2 / NT}}{MR}$	–
Density of trees per hectare	DT	$(10000 \cdot NT)/(AP \cdot pixel\ size)$	Trees / ha
Accumulated digital number of the trees	ADNT	$\sum_{i=1}^{NT} ADN_i$	DN (pixel value)
Accumulated digital number of the parcel	ADNP	Summatory of the DN of the pixels in the parcel	DN (pixel value)
Average digital number of the trees	MDNT	$ADNT/ACT$	DN (pixel value)
Average digital number of the parcel	MDNP	$ADNP/AP$	DN (pixel value)
Size of the planting pattern	SPP1, SPP2	Median of the distances between the lines in the two main directions	Meters
Angular difference between the directions of the planting pattern	ADPP	Difference between the two main directions	Degrees

V – Tree segmentation assessment

In order to evaluate the quality of the tree segmentation, the automatically obtained area covered by trees must be compared with reference data obtained with field measurements or manual digitization over the aerial orthoimages. Comparison results are commonly expressed by means of the branching factor, the miss factor and the quality percentage. The branching factor (Equation 4) is a measure of the over-detection of tree cover areas. The more accurate the detection, the closer the value is to zero. The miss factor (Equation 5) indicates the omission error in the detection of tree cover areas. These quality metrics are closely related to the boundary delineation performance of the tree extraction methodology. The quality percentage (Equation 6) measures the absolute quality of the detection model by combining aspects of boundary delineation accuracy and tree detection rate to summarize the system performance (Hermosilla *et al.*, 2011).

$$BF = \frac{100 \cdot FP}{TP + FN} \quad (4)$$

$$MF = \frac{100 \cdot FN}{TP + FN} \quad (5)$$

$$QP = \frac{100 \cdot TP}{TP + FP + FN} \quad (6)$$

These metrics are derived from the True Positive (TP), False Positive (FP) and False Negative (FN) values. TP represents those pixels corresponding to trees that are correctly detected, FP are those pixels not corresponding to trees but erroneously selected as trees, and FN represent the pixels corresponding to trees that are not detected (Fig. 10). The quality percentages of the area covered by trees in our study area range from 70% to 90%, obtaining the best results in the case of adult citrus trees.

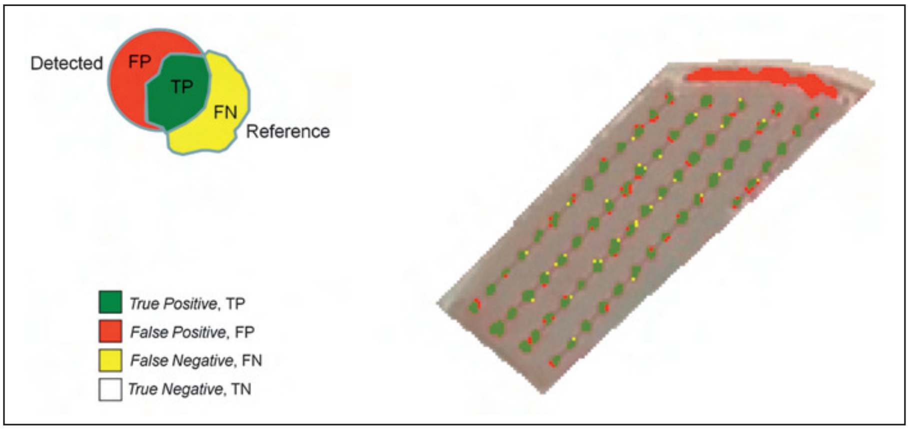


Fig. 10. Representation of the metrics used for evaluation (left) and example of their application to a citrus plot.

Planting pattern extraction assessment can be expressed by means of the root-mean-square error (Equation 7):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(d_i - d_{iobs})^2}{n}} \qquad (7)$$

where n is the number of parcels, d_{iobs} is the observed dimension of the planting pattern and d_i is the predicted dimension automatically obtained. The overall performance of the method shows that trees are located with a mean error of 40 cm, and plantation patterns determined with a root-mean-square error of 22 cm.

VI – Conclusions

This work presents an automated methodology based on digital image processing of high spatial resolution multispectral imagery for computing a set of per-tree and per-parcel agronomic parameters that exhaustively characterize tree crops. This methodology is based on common image processing tools and it has been tested over citrus orchards in the province of Valencia (Spain). High spatial resolution multispectral aerial images (0.5 m/pixel) have been used in the tests, obtaining accurate results in the estimation of agronomic parameters. The quality percentages of the area covered by trees range from 70% to 90%, obtaining the best results in adult citrus trees, being more discrete in the case of young trees. The same methodology could be applied using high-resolution satellite imagery, expecting to obtain similar results.

These techniques can be massively applied to large agricultural databases in order to extract information regarding tree location, tree counting, crown size, canopy cover or tree spatial arrangement. This information, combined with precision agriculture techniques, can be used to improve the efficiency of irrigation and fertilization processes, detection of crop diseases, assessment of crop weather damages, harvest estimation, etc. Additionally, these methods may support the updating processes of agricultural inventories, and the parameters presented can be used as input information for semi-automatic parcel-based classification of agricultural databases, reducing field work or manual interpretation of the images, which are time consuming and expensive.

Acknowledgments

The authors appreciate the financial support provided by the SUDOE program (TELERIEG Project SOE1/P2/E082), and the Spanish Ministry of Science and Innovation and FEDER in the framework of the project CGL2010-19591/BTE.

References

Culvenor D.S., 2002. TIDA: an algorithm for the delineation of tree crowns in high spatial resolution remotely sensed imagery. In: *Computers & Geosciences*, 28, p. 33-44.

Dralle K. and Rudemo M., 1997. Stem number estimation by kernel smoothing of aerial photos. In: *Canadian Journal of Forest Research,* 26, p.1228-1236.

Du Q., Orduyilmaz A., Yang C. and Everitt J.H., 2005. Detecting citrus tree size, centroid, and health conditions from airborne high-spatial-resolution multispectral imagery. In: *Proceedings of ASPRS 2005 Annual Conference "Geospatial Goes Global: From Your Neighborhood to the Whole Planet",* March 7-11, Baltimore, Maryland.

Erikson M., 2004. Species classification of individually segmented tree crowns in high-resolution aerial images using radiometric and morphologic image measures. In: *Remote Sensing of Environment*, 91, p. 469-477.

Erikson M. and Olofsson K., 2005. Comparison of three individual tree crown detection methods. In: *Machine Vision and Applications*, 16 (4), p. 258-265.

García Torres L., Peña-Barragán J.M., López-Granados F., Jurado-Expósito M. and Fernández-Escobar R., 2008. Automatic assessment of agro-environmental indicators from remotely sensed images of tree orchards and its evaluation using olive plantations. In: *Computers and Electronics in Agriculture*, 61, p. 179-191.

Gougeon F.A., 1995. A crown-following approach to the automatic delineation of individual tree crowns in high spatial resolution aerial images. In: *Canadian Journal of Remote Sensing*, 21(3), p. 274-284.

Hermosilla T., Ruiz L.A., Recio J.A. and Estornell J., 2011. Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data. In: *Remote Sensing*, 3(6), p.1188-1210.

Hough P.V.C., 1962. Methods and means for recognizing complex patterns. U.S. Patent No. 3069654.

Leckie D.G., Gougeon F.A., Walsworth N. and Paradine D., 2003. Stand delineation and composition estimation using semi-automated individual tree crown analysis. In: *Remote Sensing of Environment*, 85, p. 355-369.

Mazzetto F., Calcante A., Mena A. and Vercesi A., 2010. Integration of optical and analogue sensors for monitoring canopy health and vigour in precision viticulture. In: *Precision Agriculture*, 11, p. 636-649.

Pollock R., 1996. The automatic recognition of individual trees in aerial images of forests based on a synthetic tree crown model. PhD Thesis, Dept. Computer Science, University of British Columbia, Vancouver, Canada.

Pouliot D.A., King D.J., Bell F.W. and Pitt D.G., 2002. Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. In: *Remote Sensing of Environment*, 82, p. 322-334.

Recio J.A., 2009. Técnicas de extracción de características y clasificación de imágenes orientada a objetos aplicadas a la actualización de bases de datos de ocupación del suelo. PhD Thesis. Universitat Politecnica de Valencia, Valencia, Spain.

Ruiz L.A., Recio J.A. and Hermosilla T., 2007. Methods for automatic extraction of regularity patterns and its application to object-oriented image classification. In: *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume 36, 3/W49A, p. 117-121.

Ruiz L.A., Recio J.A., Fernández-Sarría A. and Hermosilla T., 2011. A feature extraction software tool for agricultural object-based image analysis. In: *Computers and Electronics in Agriculture*, 76, p. 284-296.

Viau A.A, Jang J.D, Payan V. and Devost A., 2005. The use of airborne Lidar and multispectral sensors for orchard trees inventory and characterization. In: *Proceedings of Information and Technology for Sustainable Fruit and Vegetable Production FRUTIC05*, 12-16 September, Montpellier France, p. 689-698.

Wang J., Sammis T.W., Andales A.A., Simmons L.J., Gutschick V.P. and Miller D.R., 2007. Crop coefficients of open-canopy pecan orchards. In: *Agricultural Water Management*, 88, p. 253-262.

Wulder M., Niemann K.O. and Goodenough D.G., 2000. Local maximum filtering for the extraction of tree locations and basal area from high spatial resolution imagery. In: *Remote Sensing of Environment*, 73, p. 103-114.